The SWOT Mission and Virtual Mission

Modeling SWOT measurements with the LISFLOOD model

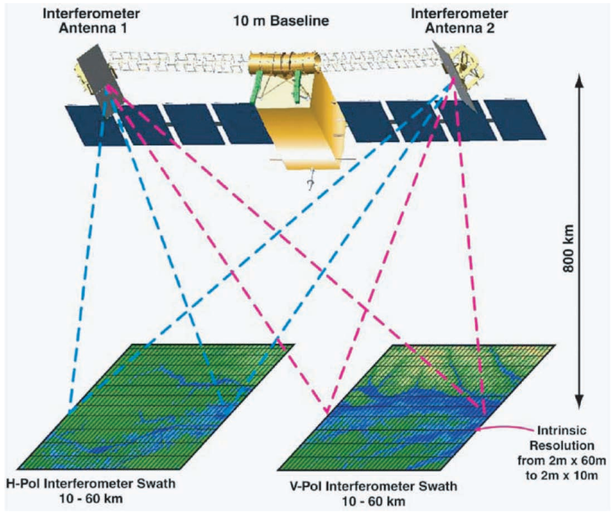
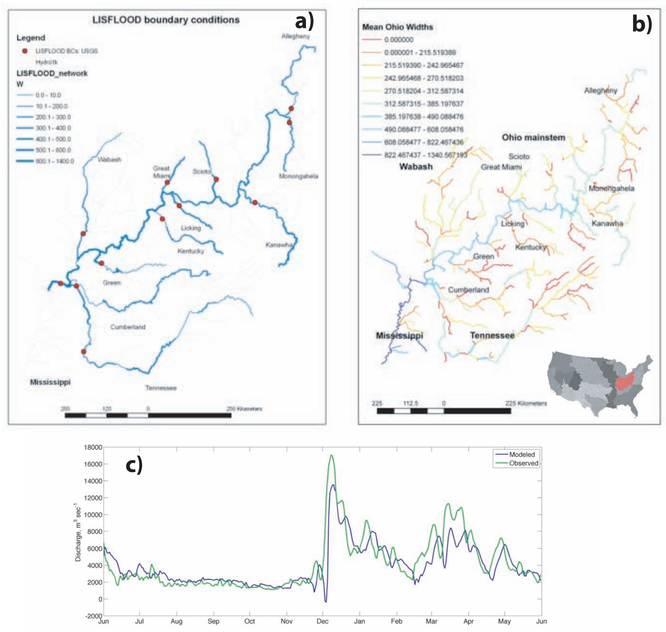


Figure 1. The Surface Water and Ocean Topography (SWOT) mission will measure inundated area and water elevation (h) for inland water surfaces, from which water slope ($\partial h/\partial x$) and temporal change ($\partial h/\partial t$) are derived. From these fundamental measurements, surface water storage change and river discharge will be calculated, two principal components of the water cycle. SWOT has been recommended by the Deacadal Survey for a launch date timeframe between 2013-2016. A key technology of the SWOT mission is a Ka-band Radar INterferometer (KaRIN) which is a near-nadir viewing, 120 km wideswath based instrument that uses interferometric SAR processing of the returned pulses to yield single-look 5m azimuth and 10m to 70m range resolution, with an elevation accuracy of approximately 50 cm. Figure from Alsdorf et al. (2007).

Figure 2. The SWOT Virtual Mission is a collaboration between CNES, NASA JPL, UW, OSU, et al., and includes modeling and assimilation studies. Goals include risk reduction, demonstrating example SWOT products, defining science traceability, and error budgets for the primary science products. In this study, SWOT observations are simulated using the LISFLOOD hydrodynamic model (Bates and de Roo, 2000), forced by USGS gages (a) on eleven of the major tributaries of the Ohio River. The model implements the diffusion wave approximation (eqn. below). Channel width was obtained from a Landsat classification, and used wirh Hydro1K steamline data (b) aggregated to 1 km spatial resolution. The resulting downstream discharge timeseries is shown (c).

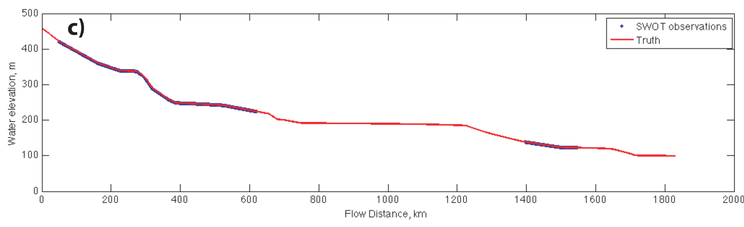


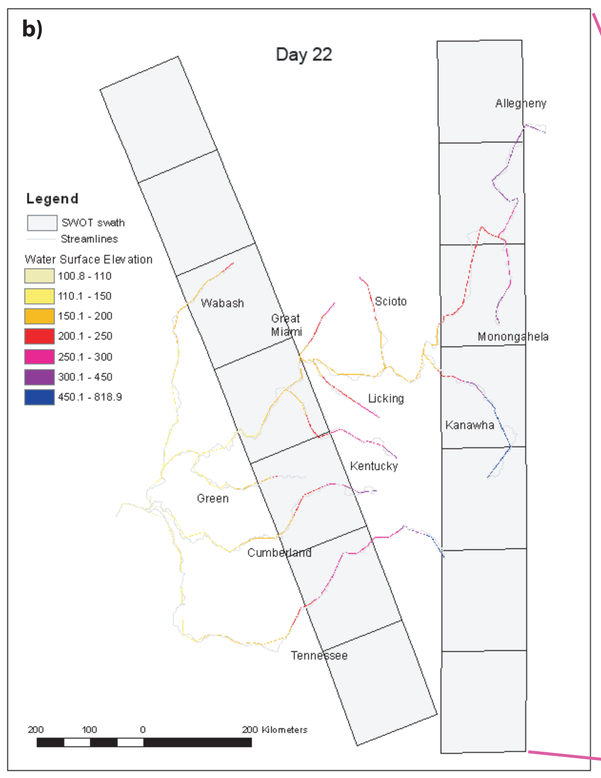
$$Q = \frac{1}{n} w z^{5/3} (S - \frac{dz}{dx})^{1/2}$$

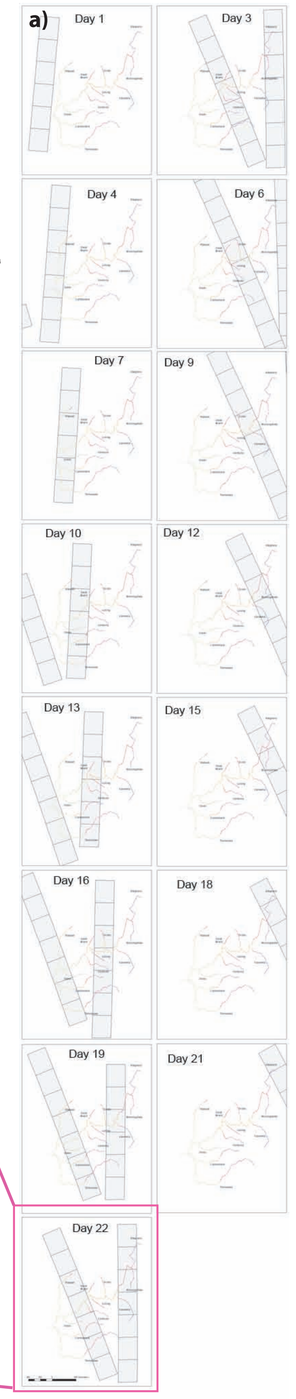
Simulated SWOT observations

Observations of Water Surface Elevation

Figure 3. The LISFLOOD model is used to predict water surface elevations (WSE), which are space-time sampled based on SWOT orbits under investigation. Sampling of WSE based on a 22-day orbit is shown in a) and b). The SWOT observations are obtained by perturbing these elevations based on random noise, assuming that 50 m SWOT pixels will have errors with standard deviation of approximately 50 cm.







Estimating river discharge from SWOT measurements

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Estimating Depth

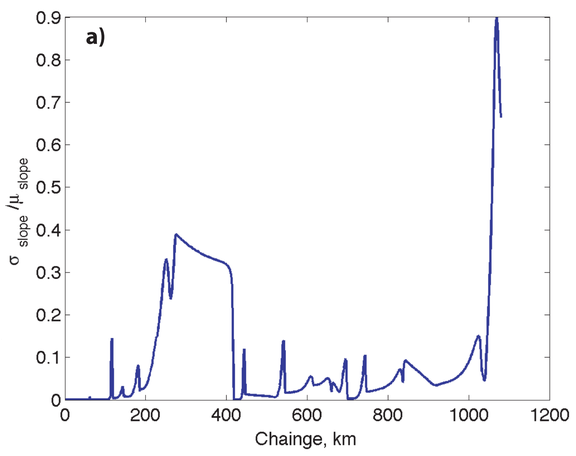
A first attempt to invert SWOT observations to find depth

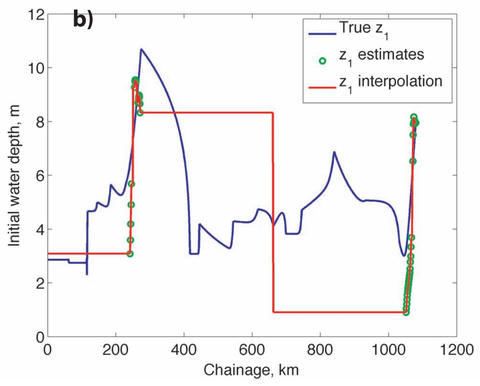
Figure 4. In order to estimate discharge from WSE observations, an estimate of channel bed elevation or an estimate of the intial water depth is required. Under two assumptions, the SWOT WSE elevation timeseries can be interrogated to yield estimates of initial depth: i) flow hydraulics can be approximated by kinematic wave approximation, and ii) steady flow. We evaluated these assumptions and found that they held within 10 % error about 95 % of the time, for the model setup described above.

The method relies, however, on slope timeseries variability. We calculared the slope time series coefficient of variation for each pixel along the Tennessee River (a). Unless the coefficient of variation is greater than around 0.2, the method is not used.

Where the method is utilized, estimates are not always accurate (b). New mehods for depth estimation will be explored, including data assimilation-based approaches, width-to-depth algorithms, and constraints based on geomorphology.

However, the current estimate is useful as a worst-case scenario, and for visualizing how error in depth estimates propagate into discharge estimates.

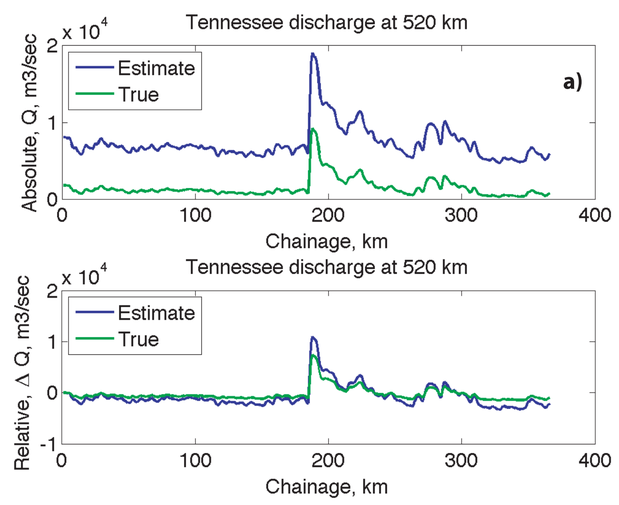




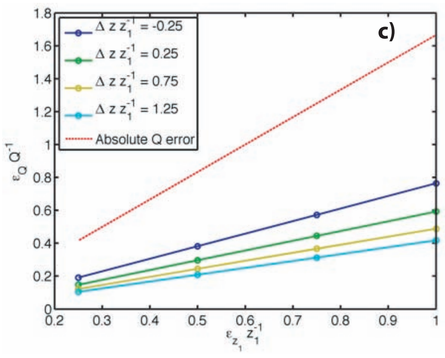
Estimating Discharge

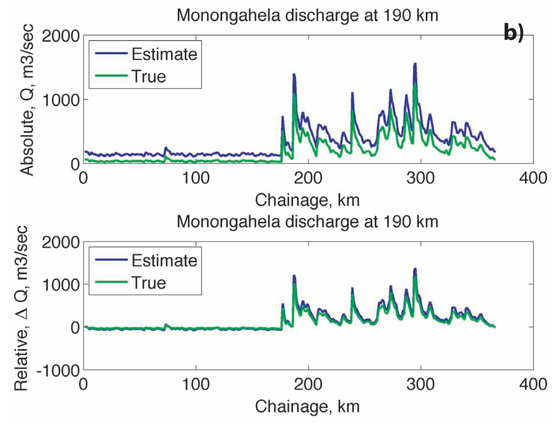
Quantifying expected errors

Figure 5. The relative and absolute discharge errors for the Tennessee (a) and Monongahela (b) rivers are shown for individual pixels along the river. The depth error is 5.0 meters (200 %) for the Tennessee and 0.5 meters (100 %) for the Monongahela rivers. These depth errors lead to incorrect discharge means. ***The discharge variations, however, are effectively captured, even for this worst case estimate of river depth.*** The mechanism for this is clear from the equations, below, for absolute (left) and relative (right) discharge error due to depth error. The sensitivity of these metrics is shown in (c), below. Depth error is amplified by 1.6 for absolute discharge. For relative discharge, depth error is damped. In order to achieve 20 % accuracy for relative discharge, depth error must be less than 40 %.



$$\frac{\varepsilon_Q}{Q} = \frac{5}{3}\frac{\varepsilon_z}{z} \qquad \frac{\varepsilon_{\Delta Q}}{Q} = \frac{5}{3}\frac{\varepsilon_z}{z}\frac{\left[\left(\frac{\Delta z}{z}\right)^{\frac{2}{3}} - 1\right]}{\left[\left(\frac{\Delta z}{z}\right)^{\frac{5}{3}} - 1\right]}$$





Acknowledgments

Funded by the NASA Terrestrial Hydrology Program, the NASA Physical Oceanography Program and the OSU Climate, Water, and Carbon Program.

References

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